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Farshid Vahid, João Victor Issler

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Common Cycles and the Importance of Transitory Shocks to Macroeconomic Aggregates^a

João Victor Issler

Graduate School of Economics - EPGE

Getúlio Vargas Foundation

Praia de Botafogo 190 - 1125

Rio de Janeiro, RJ 22253-900, Brazil

jissler@fgv.br

Farshid Vahid

Texas A&M University

Department of Economics

College Station, TX 77843-4228, USA

fv@econ4.tamu.edu

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Abstract

Although there has been substantial research using long-run comovement (cointegration) restrictions in the empirical macroeconomics literature, little or no work has been done investigating the existence of short-run comovement (common cycles) restrictions and discussing their implications.

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In this paper we first investigate the existence of common cycles in a aggregate data set comprising per-capita output, consumption, and investment. Later we discuss their usefulness in measuring the relative importance of transitory shocks. We show that, taking into account common-cycle restrictions, transitory shocks are more important than previously thought at business-cycle horizons. The central argument relies on efficiency gains from imposing these short-run restrictions on the estimation of the dynamic model. Finally, we discuss how the evidence here and elsewhere can be interpreted to support the view that nominal shocks may be important in the short run.

1. Introduction

It is a well known stylized fact in macroeconomics that economic data display co-movement. For example, Lucas (1977, section 2) reports that output movements across broadly defined sectors have high coherence. On the other hand, Kosobud and Klein (1961) document that aggregate consumption, investment and output follow balanced growth paths. While the first observation is a statement about short-run co-movement, which imposes restrictions on transitional dynamics of sectoral outputs, the second is a statement about long-run co-movement, imposing the restriction that macroeconomic aggregates cannot drift apart over time. These two types of restrictions play an important role in determining the dynamic behavior of macroeconomic time series.

Up to the present, using the econometric concept of cointegration (Engle and Granger (1987)), there has been a fair amount of research on long-run co-movement and its implications, which has shown convincingly that macroeconomic aggregates are cointegrated. Long-run restrictions have been largely used in econometrics for several purposes including estimation (Engle and Granger) and forecasting (Engle and Yoo (1987)). In the applied macroeconomics literature they have been used for the structural identification of economic shocks (Blanchard and Quah (1989) and King et al. (1991) inter-alia). In Blanchard and Quah, permanent shocks to output with no effect on unemployment are labelled 'supply' shocks whereas in King et al. the permanent shock with identical impact on output, consumption and investment is labelled 'productivity' shock. Both then proceed to measure the relative importance of permanent shocks in variance decomposition and impulse-response exercises. A similar strategy has recently been followed by

Gall (1996), who uses long run restrictions to identify 'productivity' shocks and examine how the predictions of a class of Real-Business Cycle models fit the data.

Although the use of low-frequency (cointegration) restrictions to decompose economic series into trend and cycles is widely used, this is by no means the only type of restriction that can be employed to that end. High-frequency restrictions (common cycles) can also be used in conjunction with cointegration restrictions whenever the latter exist. This was initially shown by Vahid and Engle (1993), who proposed the use of the common trend and common cycles method, later applied to a sectoral output data set by Engle and Issler (1995); see also Engle and Kozicki (1993) for a broader view of these 'common features'.

For a given data set, the joint use of common trend and common cycle restrictions to identify permanent and transitory shocks has a clear advantage over the use of common trend restrictions alone. First, there is the econometric issue of relative efficiency. Obviously, if common cycle restrictions are correctly imposed, estimates of the dynamic model (usually a Vector Autoregression) are more precise, leading to a more precise measurement of the relative importance of permanent and transitory shocks. Indeed, if two series have a common cycle their impulse-response functions are exactly colinear (Vahid and Engle (1997)). Thus variance decomposition and impulse-response calculations will be based on a reduced set of parameters. Second, there is the issue of the horizon when measuring the relative importance of shocks. For both methods the relative importance of permanent and transitory shocks should not differ much for long horizons since both impose the same long run restrictions. However, they have the potential to be different for short horizons because restrictions on short-run dynamics are imposed by only one of them.

This potential distinction is important for two reasons. On the one hand, the real usefulness of time series models is in their predictions at business cycle horizons since predictions further into the future are less precise and are also discounted more heavily by economic agents. On the other hand, while most researchers agree that nominal shocks have a limited (or no) effect on the long run behavior of macroeconomic aggregates, there is no agreement on their effect at business cycle horizons. This is why the relative efficiency result matters: a method using common trend and common cycle restrictions will deliver a more precise measurement of the relative importance of permanent and transitory shocks for the horizon that agents care most about and for which debate in the literature continues.

The goal of this paper is to examine whether U.S. per-capita output, consumption, and investment share common cycles using the common trend and common cycles method discussed in Vahid and Engle (1993). There, long-run co-movement is characterized as common stochastic trends and short-run co-movement is characterized as common cyclical components that are synchronized in phase but may have different amplitudes. Using efficient estimates of a vector autoregressive model which is restricted to produce common trends and common cycles we calculate the relative importance of permanent and transitory shocks. We later confirm the efficiency gains for our data set in an out-of-sample forecasting exercise.

Investigating the existence of common cycles is interesting in its own right, given that this is a theoretical implication of several dynamic macroeconomic models. Examples of these models are provided below. Using a more efficient trend-cycled decomposition of the data we are able to answer more precisely a key question in macroeconomics considered, among others, by Nelson and Plosser (1982), Watson (1986), Campbell and Mankiw (1987), Cochrane (1988, 1994), King et al. (1991), and Gali (1996): what is the relative importance of permanent and transitory shocks in explaining the variation of macroeconomic data?

Our empirical findings confirm the presence of common cycles in the data. The variance decomposition results show that, for output and investment, transitory shocks are important in explaining their variation. On the other hand, permanent shocks are the most important source of variation for consumption whose behavior is close to a martingale (Hall (1978) and Flavin (1981)). Contrasting our variance decomposition results with those of King et al. (1991), who only considered cointegration restrictions to identify permanent and transitory shocks illustrates that ignoring common cycle restrictions lead to nontrivial differences in the relative importance of transitory shocks. Indeed, we find transitory shocks to be more important than previous research has found. This is true especially at business cycle horizons, illustrating the advantage of the method used here. These findings are consistent with the recent results in Gali (1996) - showing that nominal (transitory) shocks are critical in explaining several features of aggregate data for G-7 countries and of den Haan (1996) - showing that demand shocks may be relevant for explaining the conditional correlations of output and prices and of hours and real wages in the short run.

Section 2 discusses several dynamic macroeconomic models that deliver common trends and common cycles for macroeconomic aggregates. Section 3 discusses

testing for common trends and cycles as well as the estimation of dynamic systems under long and short-run co-movement restrictions. A detailed explanation of the methodology used is presented in the Appendix. Section 4 presents empirical results and Section 5 concludes.

2. Theory and Testable Implications

Common trends and common cycles appear in the macroeconomic literature in several theoretical models. Here we discuss a few examples. In the dynamic stochastic general equilibrium model of King, Plosser, and Rebelo (1988), output, consumption and investment have a common trend¹ and a common cycle as a result of the optimizing behavior of the representative agent. Cointegration comes from having a common forcing variable (productivity) and a common cycle arises from the fact that the transitional dynamics of the system is a (linear) function of a unique factor - the deviation of the capital stock from its steady state value. Although these results are obtained under log utility, full depreciation of the capital stock, and Cobb-Douglas technology, they can be generalized for a variety of parameterizations under a quadratic approximation of the value function. The closed-form solutions for the logarithms of output, consumption and investment are respectively:

$$\begin{aligned}\log(Y_t) &= \log(X_t^p) + \bar{y} + \frac{1}{2} \gamma_k k_t^2 \\ \log(C_t) &= \log(X_t^p) + \bar{c} + \frac{1}{2} \alpha_k k_t^2 \\ \log(I_t) &= \log(X_t^p) + \bar{i} + \frac{1}{2} \alpha_k k_t^2\end{aligned}\quad (2.1)$$

where $\log(X_t^p) = \log(X_{t-1}^p) + \varepsilon_t^p$ is the random-walk productivity process in production, \bar{y} , \bar{c} and \bar{i} are the steady-state values of $\log(Y_t = X_t^p)$, $\log(C_t = X_t^p)$, and $\log(I_t = X_t^p)$ respectively, and $\frac{1}{2} \alpha_j$, $j = y, c, i$ is the elasticity of variable j with respect to deviations of the capital stock from its stationary value k_t^* ². From

¹ The same result is true using the endogenous growth model of Romer (1986). This makes these two models observationally equivalent in cointegrating tests.

² As noted by King, Plosser and Rebelo (1988), the above theoretical model is too simplistic to be taken as a full characterization of the data-generating process, since its only source of randomness is the productivity shock, making the system in (2.1) stochastically singular. There is an imbedded identity in this system:

$$(\alpha_{ik} - \alpha_{ck}) (\log(Y_t) - \bar{y}) = (\alpha_{ik} - \alpha_{yk}) (\log(C_t) - \bar{c}) + (\alpha_{yk} - \alpha_{ck}) (\log(I_t) - \bar{i})$$

(2.1) it is straightforward to verify that these variables have a common trend ($\log(X_t^p)$), and a common cycle \mathcal{R}_t . The following linear combinations have no trend:

$$\begin{aligned}\log(Y_t) - \log(C_t) \\ \log(Y_t) - \log(I_t); \end{aligned} \quad (2.2)$$

and $\log(Y_t)$, $\log(C_t)$, and $\log(I_t)$ are cointegrated in the sense of Engle and Granger (1987), with (2.2) showing two (linearly) independent cointegrating relationships. The following linear combinations have no cycle:

$$\begin{aligned}\frac{1}{4}_K \log(Y_t) - \frac{1}{4}_{JK} \log(C_t) \\ \frac{1}{4}_{IK} \log(Y_t) - \frac{1}{4}_{JK} \log(I_t); \end{aligned} \quad (2.3)$$

and $\log(Y_t)$, $\log(C_t)$, and $\log(I_t)$ have a common cycle in the sense of Vahid and Engle (1993), with (2.3) showing two (linearly) independent cofeature combinations.

To elaborate more on this issue, consider the first differences of the logarithm (i.e. growth rate) of the system (2.1):

$$\begin{aligned}\Delta \log(Y_t) &= \mathcal{Z}_t^p + \frac{1}{4}_{JK} \Delta \mathcal{R}_t \\ \Delta \log(C_t) &= \mathcal{Z}_t^p + \frac{1}{4}_K \Delta \mathcal{R}_t \\ \Delta \log(I_t) &= \mathcal{Z}_t^p + \frac{1}{4}_{IK} \Delta \mathcal{R}_t; \end{aligned} \quad (2.4)$$

Given that \mathcal{Z}_t^p is white noise, equations (2.4) show that all the (short-run) serial correlation of macroeconomic aggregates is due to a single common factor $\Delta \mathcal{R}_t$. Thus 'cycles' in $\Delta \log(Y_t)$, $\Delta \log(C_t)$, and $\Delta \log(I_t)$ are synchronized, but amplitudes may differ since the $\frac{1}{4}_{JK}$'s may be different.

In the class of partial equilibrium models Campbell (1987) shows that saving (S_t) can be written as a function of expected future income variations $E_t(\Delta Y_{t+s})$:

$$S_t = \sum_{s=1}^{\infty} \frac{1}{2}^s E_t(\Delta Y_{t+s}); \quad (2.5)$$

where E_t is the conditional expectation operator using information up to period t and $\frac{1}{2}$ is the one-period discount factor for future income (Y_{t+s}). Since saving is the difference between disposable income and consumption, which by (2.5)

is stationary, consumption and disposable income must cointegrate if Y_t is an integrated series

For partial equilibrium models in the tradition of Hall (1978) and Flavin (1981), consumption is a martingale. Thus its first difference has no serial correlation even if the (differenced) income process is serially correlated. Thus consumption and income fail to have common cycles. However, if a proportion of the population follows the "rule of thumb" of consuming their income entirely in every period, Campbell and Mankiw (1989) show that aggregate consumption and aggregate income will have a common cycle as a result of this myopic behavior.

Letting $(C_{1t}; Y_{1t})$ and $(C_{2t}; Y_{2t})$ be the consumption-income pairs of "permanent income" and "myopic" agents respectively, and letting $(C_t; Y_t)$ denote the aggregate consumption-income pair, with $\alpha = \frac{Y_{2t}}{Y_t}$ measuring the income proportion of myopic agents, Campbell and Mankiw show that:

$$\Delta C_t = \alpha \Delta Y_t + (1 - \alpha) \epsilon_t \quad (2.6)$$

where ϵ_t is proportional to the innovation in Y_{1t} . Since ϵ_t is unpredictable, and since ΔY_t is usually serially correlated, equation (2.6) shows that all the serial correlation of ΔC_t comes from ΔY_t . In this case, the cycles of Y_t and C_t are synchronized. Notice that the amplitude of the cycle in consumption is an increasing function of the importance of myopic agents (α).

The example is used above ~~to~~ ^{to} show that common trends and common cycles for macroeconomic aggregates can be the result of either optimal or myopic behavior, and are a feature of partial and general equilibrium models. This in itself motivates their investigation. There is an additional reason to study them: common trends and common cycles represent respectively low- and high-frequency restrictions on multivariate data sets. Whenever these restrictions are present, imposing them can considerably reduce the number of estimated parameters in time series models, leading to efficiency gains in estimation.

3. Estimation and Testing

This section is ~~used~~ ^{used} for testing for common trends and cycles and implications of their existence for the efficient estimation of dynamic models of macroeconomic aggregates. We present in the Appendix the formal definitions of common trends and cycles, different representations for macroeconomic aggregates under their presence, and the trend-cycle decomposition method used here.

Following King et al. (1991), it is useful to note that the reduced form for a (linear) system containing (the log of) output, consumption and investment is nested in the general dynamic framework of Vector Autoregressions (VAR's). If there are common trends in the data, the VAR has cointegration restrictions as shown by Engle and Granger (1987). Thus we can reduce the number of parameters of the dynamic representation by estimating a Vector Error-Correction Model (VECM) which takes these restrictions into account. Common cycles impose extra restrictions on this dynamic system (Vahid and Engle (1993)). In this case it is possible to further reduce the number of parameters in the VECM. Efficient estimation requires estimating a restricted VECM, which takes into account the common cyclical dynamics present in the first differences of the data; see equations (2.4) and (2.6) for example.

Tests for cointegration are not discussed in any length here, since this literature is now well known. We employ Johansen's (1988, 1991) technique, which estimates the number of linearly independent cointegrating vectors (r). Testing for common cycles amounts to searching for independent linear combinations of the (level of the) variables that are random walks, thus cycle free. The test therefore is a search for linear combinations of the first differences of the variables whose correlation with the elements of the past information set in the right-hand side of the VECM will be zero. This can be done by testing for zero canonical correlations between the first differences of the variables and the elements of the past information set. This test is in effect testing for cointegration restrictions on the parameters of the VECM; see Vahid and Engle (1993).

Assuming that output, consumption and investment have one stochastic trend³, and that the two cointegrating relationships are respectively $(\log(C_t - Y_t))$ and $(\log(I_t - Y_t))$, the test for common cycles and the fully efficient estimation of the restricted VECM entail the following steps

1. Determine p , the required number of lags in the VECM that adequately captures the dynamics of the system.
2. Compute⁴ the sample squared canonical correlations between

³This is not to say that the common cycles test is not applicable when variables have deterministic rather than stochastic trends. In fact, common cycles are about comovement in detrended series, regardless of the form of the trend. We explain the procedure for the case of stochastic trends because it is more relevant to the present paper. The case of deterministic trend is straightforward.

⁴This can be easily done using PROC CANCORR in SAS. Alternatively, a GAUSS code

$\log(Y_t); \log(C_t); \log(I_t)$ and
 $\log(C_{t-1}=Y_{t-1}); \log(I_{t-1}=Y_{t-1}); \log(Y_{t-1}); \log(C_{t-1}); \log(I_{t-1});$
 $\dots; \log(Y_{t-p}); \log(C_{t-p}); \log(I_{t-p})$, labelled $s_i, i = 1, \dots, n$, where
 n is the number of variables in the system (n equals three in this case).

- Test whether the r smallest canonical correlations are zero by computing the statistic:

$$-2 \sum_{i=1}^r \log(1 - \lambda_i^2);$$

which has a limiting χ^2 distribution with $s(n-p-r) - s(n-j-s)$ degrees of freedom under the null, where r is the number of cointegrating relationships (r equals two in our example). In the absence of identities in the system, the maximum number of zero canonical correlations that can possibly exist is $n-j-r$ ($n-j-r$ is one in our example, since we assumed two cointegrating vectors).

- Suppose that s zero canonical correlations were found in the previous step. Use these s contemporaneous relationships between the first differences as s pseudo-structural equations in a system of simultaneous equations. Augment them with $n-j-s$ equations from the VECM and estimate the system using full information maximum likelihood (FIML). The restricted VECM will be the reduced form of this pseudo-structural system.

In addition to leading to a parsimonious model, the existence of unpredictable linear combinations of the first differences may allow us to readily identify the shocks with permanent effects. Take, for example, the model of King, Plosser, and Rebelo (1988) discussed above. There,

$$\begin{aligned}
 \frac{1}{2} \Delta \log(Y_t) &= \frac{1}{2} \Delta \log(C_t) = (\frac{1}{2} \Delta \log(Y_t) - \frac{1}{2} \Delta \log(C_t))^{2p}_t \\
 \frac{1}{2} \Delta \log(Y_t) &= \frac{1}{2} \Delta \log(I_t) = (\frac{1}{2} \Delta \log(Y_t) - \frac{1}{2} \Delta \log(I_t))^{2p}_t
 \end{aligned} \quad (3.1)$$

Either of these two equations identify $2p_t$, given knowledge of $\frac{1}{2} \Delta \log(Y_t)$, $\frac{1}{2} \Delta \log(C_t)$, and $\frac{1}{2} \Delta \log(I_t)$. Along the same lines for the model of Campbell and Mankiw (1989), we have:

$$C_t = (1 - \alpha) Y_t + \alpha C_{t-1} \quad (3.2)$$

for calculating canonical correlations and the test statistic for common cycles is available upon request.

which, given ϵ_t , identifies ϵ_t , the shock to permanent income of the type one consumer.

This form of shock identification is much simpler than the method employed by King et al. (1991), since it only requires knowledge of cointegrating and cofeature vectors (see the Appendix). The latter requires inverting the autoregressive representation. Also, since we impose testable long and short-run restrictions to the VAR, we achieve more efficient estimates of VAR coefficients. This leads to more efficient estimates of impulse responses and variance decompositions, since these are based on a more parsimonious model.

It is important to understand the possible differences in results from using the two methods. If the long-run restrictions imposed by both methods are the same, impulse-response and variance-decomposition results will be similar for long horizons (being exactly the same in the infinite horizon). However, they have the potential to differ at business-cycle horizons, since only the method used here imposes short-run co-movement restrictions. Given the efficiency gains discussed above, our variance-decomposition and impulse-response results will be more precise at short horizons. As argued above, this is important for economic agents who discount future events more heavily, and thus care more about what happens at business-cycle horizons. It is also important as a tool in evaluating theoretical models in short horizons, especially regarding the importance of nominal shocks.

Since the efficiency-gains result is theoretical, we compare out-of-sample forecasts between the restricted and the unrestricted VECM to substantiate that these gains are relevant for the present data set. We find that the former performs better.

4. Empirical Evidence

The data being analyzed consist of (log) real U.S. per-capita private output - y , personal consumption per-capita - c , and fixed investment per-capita - i . The data were extracted from Citibase on a quarterly frequency⁵. Although Citibase has data available from 1947:1 to 1994:2, we used only 1947:1 through 1988:4 in estimation, in order to match the sample period used in King et al. (1991), thus making results directly comparable.

⁵Using the Citibase mnemonics (1995) for the series, the precise definitions are: $G CQ$ - consumption, $G IFQ$ - investment, and $G N PQ$ - $G G EQ$ - output. Population series mnemonics is $G POP$.

The plot of (logged) per-capita real output, consumption and investment is presented in Figure 1. There are two striking characteristics. First, the data are extremely smooth (typical of I(1) data) and appear to be trending together in the long run. Second, the data show similar short-run behavior: during recessions all three aggregates drop. However, investment drops much more than consumption and output, and the latter drops more than consumption - the most insensitive series to recessions.

Tests for cointegration were performed using Johansen's (1988, 1991) technique and are presented in Table 1. Critical values were extracted from Osterwald-Lenum (1992). We conclude that the cointegrating rank r is two. This implies the existence of a common stochastic trend for output, consumption and investment. Table 1 also presents the point estimates of a normalized version of these two vectors. They are very close to $(1; 1; 0)'$ and $(1; 0; 1)'$ respectively, which implies that the consumption-output and investment-output ratios are I(0). In order to jointly test these hypotheses we use the likelihood ratio test proposed in Johansen (1991). The results of this test do not reject that $(1; 1; 0)'$ and $(1; 0; 1)'$ are a basis for the cointegrating space. These findings are consistent with the theoretical models mentioned above, and with the results in King et al. (1991), who used a different test for cointegration. They imply that the 'great ratios' are I(0) processes.

The next step of the testing procedure is to use canonical correlation analysis to examine whether the data have common cycles. For the common cycle test, we use the VECM with $(1; 1; 0)'$ and $(1; 0; 1)'$ as the two cointegrating vectors. We follow King et al. (1991) in conditioning on eight lags of the dependent variables in the VECM, which is enough to capture the dynamics of the system. Table 2 shows the results of the common cycle tests: the p-values for the $\hat{\Lambda}^2$ test and its F-test approximation⁶ of the null hypothesis that the current and all smaller canonical correlations are statistically zero. As noted before, the cofeature rank s is the number of statistically zero canonical correlations. At the 5% level, both tests cannot reject the hypothesis that the smallest canonical correlation is statistically zero, which implies that s is one. Thus, output, consumption and investment share two independent cycles and do have similar short-run fluctuations.

As is used in the Appendix, the fact that $n = r + s$ allows a special trend-cycle decomposition of the data. Since we found a common stochastic trend for our system, the trend component of output, consumption and investment

⁶The use of this approximation is suggested by Rao (1973, p. 556).

is the same, being generated by the linear combination of the data that uses the cofeature vector (the maximum likelihood estimate of the common trend is $0.42 \Phi_t + 0.87 \Phi_{t-1} + 0.29 \Phi_{t-2}$). On the other hand, these variables will have cycles that combine two distinct $I(0)$ serially correlated components which are in turn generated by the linear combination of the data using the cointegrating vectors (the great ratios); see Table 3. Plots of the trend and cycles of the data are given in Figures 2 through 4 and 5 through 7 respectively. The trend is very smooth compared to the data in levels and the cycles show a distinct pattern of serial correlation.

Three features are worth noting from these graphs. First, it seems that there is little difference between consumption and the common trend, which results in a very small cycle for that variable (Cochrane (1994)). Although consumption cannot be characterized as a random walk, thus failing Hall's (1978) test of the permanent-income hypothesis, it seems that its cyclical component is very small⁷. Similar results are achieved by Fama (1992) and Cochrane (1994), although with different techniques. Second, investment has a much more volatile cycle than output and consumption, which translates into the investment cycle having the highest amplitude of them all. This is one of the stylized facts of business cycles cited in Lucas (1977). Third, all three cycles drop during NBER recessions⁸.

The estimates of trend and cycles of the data allow us to answer a question considered important by most authors in the applied macroeconomic literature: do permanent or transitory shocks explain the bulk of the variance of aggregate data? Attempts to answer this question can be found, among others, in the work of Nelson and Plosser (1982), Watson (1986), Campbell and Mankiw (1987), Cochrane (1988, 1994), King et al. (1991), and Galí (1996). Nelson and Plosser find this issue important because they associate trends to permanent factors influencing output - such as productivity, and cycles to transitory factors - such as monetary policy.

Since the trend-innovation effects are permanent while the cycle-innovation effects are only transitory, it seems reasonable to attach importance to the trend component if the trend innovation explains a significant proportion of total forecast errors at business cycle horizons. The results of the variance decomposition of

⁷We return to this issue later, after presenting the results of the variance decomposition of innovations of the data set.

⁸Some minor exceptions are verified. The trend sometimes drops during recessions as well, but this is not a consistent pattern.

output, consumption and investment are presented in Table 4. This table shows the percentage of the variance of total forecast errors explained by permanent shocks at different horizons⁹. For output, transitory shocks explain about 50% of the forecast error variance (FEV) at the two year horizon, more than 40% at the three-year horizon and more than 30% at the four-year horizon. For shorter horizons, transitory shocks explain more than half of the FEV. In that sense, we cannot disregard the importance of the transitory component of output. The results for investment are much stronger. Transitory shocks explain most of the FEV for all tabulated finite horizons. For the one-year horizon, these shocks explain more than 90% of the FEV, and for the two-year horizon almost 80%.

The results of the variance decomposition for consumption allow discussing the permanent-income hypothesis. At the one-year horizon, the permanent component explains almost 80% of the FEV, and at the two-year horizon about 85%. The picture that emerges is that of an all-important permanent component. The plot of Figure 3 corroborates this evidence. On the one hand, if one is willing to label the permanent part of consumption as permanent income¹⁰, the variance decomposition analysis allows one to conclude that permanent income is by far the most important component of consumption. Moreover, consumption and permanent income obey long-run proportionality, an important theoretical result. On the other hand, although we found excess sensitivity in consumption e.g., Hall (1978) and Flavin (1981), consumption's transitory part has very little importance.

At this point, it is useful to compare the result of our variance decomposition with those of King et al. (1991). Since both studies used the same data and sample period, the results are directly comparable and any differences in results can be attributed to short-run co-movement restrictions being imposed by our method.

⁹Trend innovations are the first differences of the common trend. Cycle innovations are the residuals obtained by regressing cycles on the right-hand-side variables in the VECM (the lagged error-correction terms and the eight first lags of the dependent variables). Since the two innovations are correlated, we orthogonalize them, and we denote the portion of the cycle innovation orthogonal to the trend innovation as the "transitory shock". The "permanent shock" will then comprise the original trend innovation and the portion of the cycle innovation explained by the trend innovation.

¹⁰According to one view of the permanent-income hypothesis, consumption should be equal to permanent income. Since the trend in consumption and income is the same, we can think of it as the permanent part of income, or permanent income. Thus, having the common trend almost equal to consumption implies permanent income and consumption being almost identical.

King et al. results are reported in parentheses in Table 4. As expected, the major differences in results occur for short horizons (1-12 quarters): their method underestimates the contribution of the transitory portion of output and investment. The same happens for consumption for the 1-to-4-quarter horizon being reversed, however, for longer horizons. The biggest discrepancy happens for output: in their method, the permanent portion of output explains almost 60% (70%) of output variance for the one-(two-)year horizon whereas our result assigns about 40% (50%) to it. These differences are enough to change the emphasis of the variance decomposition results for output. It is clear that a much more considerable role should be attributed to sources of transitory noise. It is important to note that this result was obtained in a framework where only real variables were considered, which in itself potentially limits the role of some sources of transitory shocks e.g., monetary policy; see the results in King et al. (1991) when monetary variables are included in the VAR and also the discussion in Hansen and Heckman (1996, footnote 9).

The importance of transitory components of output was also reported by Cochrane (1994), and a similar general result is achieved by King et al. (1991), after augmenting their VAR with monetary sector variables. More recently, Gali (1996) has shown that nominal (nonpermanent) shocks are critical for explaining the conditional correlation pattern of labor productivity and employment (or hours). Moreover, these nominal shocks are responsible for the synchronized cyclical behavior of GDP and hours when the nominal-shock components of GDP and hours are ignored, these two series fail to show any distinct business cycle pattern (see Gali's Figure 6). Along the same lines, den Haan (1996) finds that output and prices are positively correlated at business cycle horizons although negatively correlated in the long run. This supports the conclusion that nominal shocks are important in the short run while real shocks are important in the long run. It also illustrates that the horizon matters for investigating the plausibility of different theories, a point also stressed by Hansen and Heckman (1996).

This body of evidence goes against the claim in Nelson and Plosser (1982) that permanent shocks are the most important source of variation for output. Although there is no doubt that this is true for long horizons, results for business cycle horizons point toward the importance of transitory shocks. If the horizon matters, it would be interesting to consider the most precise technique at short horizons and this is exactly what we have tried to provide in this paper.

Although it seems that our and more recent results show the importance of

nominal shocks at business cycle horizons it is not obvious how to interpret the evidence. Theoretical models are rarely built in terms of permanent or transitory shocks. Rather, they are built in terms of real (productivity) or nominal (monetary) shocks. Thus to test theories one has usually to impose identifying assumptions. For example, Blanchard and Quah (1989), King et al. (tri-variate system), and Galí assume that the only source of permanent shocks is productivity. Nonpermanent shocks are labelled "demand" shocks by Blanchard and Quah and Galí. However, one can certainly think of permanent demand shocks (a permanent change in preferences, for example) or of transitory supply shocks (transitory technology shocks, for example). In these cases those identifying assumptions will fail¹¹.

Although answering these issues is out of the scope of this paper, we argue that the results here and elsewhere are still useful. We rely on the reasonable assumption that permanent shocks are more likely to be real, whereas transitory shocks are more likely to be nominal. This "axiom," as far as we know, has never been properly challenged, despite the fact that more than 15 years have now elapsed since Nelson and Plosser first used it.

4.1. Post-Sample Forecasts of Per-Capita Output, Consumption and Investment

This last section compares post-sample forecasts of two econometric representations of our tri-variate system. The first is the Unrestricted VECM (U-VECM), which does not take into account short-run restrictions implied by the existence of common cycles. The second is the Restricted VECM (RVECM), which takes those restrictions into account. Sample estimates used data for output, consumption and investment from 1947:1 to 1988:4. Post-sample one-step-ahead forecasts for each representation were then calculated from 1989:1 to 1994:2, comprising 22 quarterly observations.

Estimation of the U-VECM used eight lags for all lagged dependent variables and one lag for the error-correction terms. Since it is a reduced-form, it was estimated by Least Squares. The RVECM was estimated using the same lag structure as the U-VECM, but imposing common cycle restrictions on the system.

¹¹ This, however, is not the only problem. In an economy with distortions, Basu and Fernald (1997) show that there are many sources of productivity variation unrelated to technology, which raises the issue of what is really being "identified" by the literature.

As is used in the Appendix, these restrictions can be conveniently formulated in terms of exclusion restrictions in a system of "structural"¹² equations. Thus the system was estimated using FIML, a suitable method for estimating structural forms to find the maximum likelihood estimates of the parameters.

Forecasting results are reported in Table 5, which contains the mean squared error (MSE) in forecast for each equation separately, and the determinant of the mean squared forecast error matrix, a measure of the overall forecasting performance for the system.

For the overall system, it is clear that the RVECM representation does better, with a difference in the determinant of the mean squared forecast error matrix of more than 25%. For individual equations the RVECM outperforms the UVECM in forecasting for all three series. The forecasting improvement is most remarkable for output and consumption. The empirical results achieved here confirm the theoretical prediction that restricted estimation reduces MSE whenever "true restrictions" are imposed on estimation.

5. Conclusions

This paper confirms the prediction of several theoretical models that output, consumption and investment share both a common trend and common cycles. Although common trends have been investigated and confirmed before, finding common cycles constitutes new evidence regarding this aggregate data set. As discussed above, this finding is relevant for calculating more precisely the relative importance of permanent and transitory shocks at business cycle horizons for which this issue is still controversial and which economic agents find more relevant for welfare considerations.

The results show that transitory shocks are more important than previously thought. They explain about 50% of the variation of output at the 2-year horizon, more than 40% at the 3-year horizon and more than 30% at the 4-year horizon. The results for investment are even stronger: more than 50% up to the 5-year horizon. Despite these results the permanent shock explains a very large proportion of consumption variation, providing evidence of consumption smoothing over time. The importance of transitory shocks documented here finds support in the recent research by Gali (1996) and den Haan (1996), as well as in the work

¹²"Structural" in the sense of econometrics of simultaneous equation systems.

of Cochrane (1994). It may be a sign that nominal shocks are relevant for the short-run variations of macroeconomic data.

Finally, by using a post-sample forecasting exercise, this paper establishes that ignoring common cycle restrictions in this multivariate data set can lead to a nontrivial loss of efficiency in estimating reduced-form VECM's. This can affect the precision of estimates of trends and cycles as well as the precision of impulse-response and variance decomposition exercises. Therefore, testing for common cycles should always precede econometric estimation whenever short-run co-movement restrictions are likely to be present.

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A. Co-Movement Restrictions in Dynamic Models

Before discussing the dynamic representation of the data, and the trend-cycle decomposition method we have used, we present the definitions of common trends and common cycles. For a full discussion see Engle and Granger (1987) and Vahid and Engle (1993) respectively. First, we assume that y_t is a n -vector of $I(1)$ variables with the stationary ($M A(1)$) Wold representation given by:

$$\Phi y_t = C(L)z_t; \quad (A.1)$$

where $C(L)$ is a matrix polynomial in the lag operator, L , with $C(0) = I_n$, $\sum_{k=1}^{\infty} \|C_k\| < \infty$. The vector z_t is a $n \times 1$ vector of stationary one-step-ahead linear forecast errors in y_t given information on the lagged values of y_t . We can rewrite equation (A.1) as

$$\Phi y_t = C(1)z_t + \sum_{i=1}^{\infty} C_i(L)z_t \quad (A.2)$$

where $C_i = \sum_{j=i}^{\infty} C_j$ for all i . In particular $C_0 = I_n - C(1)$.

If we integrate both sides of equation (A.2) we get:

$$\begin{aligned} y_t &= C(1) \sum_{s=0}^{t-1} z_{t-s} + \sum_{i=1}^{\infty} C_i(L) z_t \\ &= T_t + C_t \end{aligned} \quad (A.3)$$

Equation (A.3) is the multivariate version of the Beveridge-Nelson trend-cycle representation (Beveridge and Nelson (1981)). The series y_t are represented as sum of a random walk part T_t which is called the "trend" and a stationary part C_t which is called the "cycle".

Definition A.1. The variables in y_t are said to have common trends (or cointegrate) if there are r linearly independent vectors $r < n$, stacked in an $r \times n$ matrix Φ^0 , with the property that:

$$\Phi^0 C(1) = 0;$$

Definition A.2. The variables in y_t are said to have common cycles if there are s linearly independent vectors $s < n$, stacked in an $s \times n$ matrix Φ^0 , with the property that:

$$\Phi^0 \sum_{i=1}^{\infty} C_i(L) = 0;$$

Thus cointegration and common cycles represent restrictions on the elements of $C(1)$ and $C^{\pi}(L)$ respectively.

We now discuss restrictions on the dynamic autoregressive representation of economic time series arising from cointegration (common trends) and common cycles. First, we assume that y_t is generated by a Vector Autoregression (VAR):

$$y_t = \alpha_1 y_{t-1} + \dots + \alpha_p y_{t-p} + \varepsilon_t \quad (A.4)$$

If elements of y_t cointegrate, then the matrix $I + \sum_{i=1}^p \alpha_i$ must have less than full rank, which imposes cointegration restrictions on the VAR. In this case, Engle and Granger (1987) show that the system (A.4) can be written as a Vector Error-Correction model (VECM):

$$\varepsilon y_t = \alpha_1^{\pi} \varepsilon y_{t-1} + \dots + \alpha_{p-1}^{\pi} \varepsilon y_{t-p+1} + \alpha^0 \varepsilon y_{t-1} + \varepsilon_t \quad (A.5)$$

where α^0 and α^{π} are full rank matrices of order $n \times r$, r is the rank of the cointegrating space, $I + \sum_{i=1}^p \alpha_i = \alpha^0 \alpha^{\pi}$, and $\alpha_j^{\pi} = \sum_{i=j+1}^p \alpha_i$, $j = 1, \dots, p-1$. Given the cointegrating vectors stacked in α^0 , it can be seen that (A.5) parsimoniously encompasses (A.4). Conditional on knowledge of cointegrating vectors the VECM has $n^2(p-1) + n$ parameters in the conditional mean, while the VAR has $n^2 p$ parameters. Thus the former has $n(n-r)$ fewer parameters since $r < n$. If we take into account the free parameters in the cointegrating vector, the VECM has $n^2(p-1) + 2n + r^2$ mean parameters ($n-r$)² fewer than the VAR.

Vahid and Engle (1993) show that the dynamic representation of the data y_t may have additional cointegration restrictions if there are common cycles. To see this recall that the cofeature vectors α_i^0 , stacked in an $n \times n$ matrix α^0 , eliminate all serial correlation in εy_t ; i.e. $\alpha^0 \varepsilon y_t = \alpha^0 \varepsilon_t$. Since the cofeature vectors are identified only up to an invertible transformation, we can without loss of generality, rotate α^0 to have an n -dimensional identity sub-matrix

$$\alpha^0 = \begin{pmatrix} I_n \\ \alpha_{(n-s) \times s}^{\pi} \end{pmatrix} \varepsilon_s$$

Considering $\alpha^0 \varepsilon y_t = \alpha^0 \varepsilon_t$ as equations in a system, and completing the system by adding the unconstrained VECM equations for the remaining $n-s$ elements

of y_t we obtain

$$\begin{pmatrix} I_s \\ 0 \end{pmatrix}_{(n_i-s) \times s} \begin{pmatrix} \alpha \\ I_{n_i-s} \end{pmatrix} y_t = \begin{pmatrix} 0 \\ i_1 \alpha \vdots i_{p+1} \alpha \end{pmatrix}_{s \times (np+r)} y_t + \begin{pmatrix} y_{t-1} \\ \vdots \\ y_{t-p+1} \\ y_t \end{pmatrix}_{(p+1) \times 1} + v_t \quad (A.6)$$

where $i_1 \alpha$ and α represent the partitions of $i_1 \alpha$ and α respectively, corresponding to the bottom n_i reduced form VECM equations and $v_t = \begin{pmatrix} I_s \\ 0 \end{pmatrix}_{(n_i-s) \times s} \begin{pmatrix} \alpha \\ I_{n_i-s} \end{pmatrix} z_t$.

It is easy to show that (A.6) parsimoniously encompasses (A.5). Since $\begin{pmatrix} I_s \\ 0 \end{pmatrix}_{(n_i-s) \times s} \begin{pmatrix} \alpha \\ I_{n_i-s} \end{pmatrix}$ is invertible, it is possible to recover (A.5) from (A.6). Notice however that the latter has $(np+r)s$ fewer parameters.

B. Trend-Cycle Decomposition

We now discuss the trend-cycle decomposition used here. For a full discussion see Vahid and Engle (1993). From equation (A.3):

$$\begin{aligned} y_t &= C(1) \sum_{s=0}^{\infty} z_{t-s} + C(L) z_t \\ &= T_t + C_t \end{aligned} \quad (B.1)$$

Consider the special case of $n = r + s$ and stack the cofeature and the cointegrating combinations to obtain

$$\begin{pmatrix} \alpha y_t \\ \alpha y_t \end{pmatrix} = \begin{pmatrix} \alpha T_t \\ \alpha C_t \end{pmatrix} \quad (B.2)$$

The $n \times n$ matrix $A = \begin{pmatrix} \alpha \\ \alpha \end{pmatrix}$ has full rank and therefore is invertible. Partition the columns of the inverse accordingly as $A^{-1} = [\alpha^{-1} \quad \alpha^{-1}]$ and recover the common trend common cycle decomposition by pre-multiplying the cofeature and cointegrating combinations by A^{-1} :

$$y_t = A^{-1} A y_t = \alpha^{-1} (\alpha y_t) + \alpha^{-1} (\alpha y_t); \quad (B.3)$$

This implies that $T_t = \alpha_i \alpha y_t$ and $C_t = \beta_i \beta y_t$, i.e. trend and cycles are simple linear combinations of the data y_t .

Notice that the first term in (B.3) depends only on cofeature combinations while the second term is a function of cointegrating combinations only. This illustrates that the former are trend generators in this decomposition while the latter are cycle generators.

TABLE 1
COINTEGRATING RESULTS USING JOHANSEN'S(1988) TECHNIQUE

EIGENVALUES (μ_i)	TRACE TEST $-T \sum_{j \leq i} \ln(1 - \mu_j)$	CRITICAL VALUE AT 5%	NULL HYPOTHESES
0.01886	3.06	3.76	\exists at most 2 cointegrating vectors
0.07726	16.01	15.41	\exists at most 1 cointegrating vectors
0.13944	40.18	29.68	\exists at most 0 cointegrating vectors

Estimated Normalized Cointegrating Space:

$$\hat{\alpha}' = \begin{pmatrix} -1.06 & 1 & 0 \\ -1.01 & 0 & 1 \end{pmatrix}$$

Test of Restrictions in the Cointegrating Space:

$$H_0: \quad \alpha' = \begin{pmatrix} -1 & 1 & 0 \\ -1 & 0 & 1 \end{pmatrix}$$

$$\chi^2(2) = 3.856, \quad \text{p-value} = 0.1454$$

TABLE 2
CANONICAL CORRELATION ANALYSIS
COMMON-CYCLE TESTS

SQUARED CANONICAL CORRELATIONS (I_i^2)	Prob > $\chi^2(d)$ (d)	Prob.>F	NULL HYPOTHESES
0.4892	>0.0001 (78)	0.0001	Current and all smaller (I_i) are zero
0.2860	0.004 (50)	0.0226	Current and all smaller (I_i) are zero
0.1544	0.3200 (24)	0.4651	Current and all smaller (I_i) are zero

TABLE 3
TRENDS AND CYCLES AS LINEAR COMBINATIONS OF THE DATA^a

TRENDS			
VARIABLE	Y	c	i
y	0.42	0.87	-0.29
c	0.42	0.87	-0.29
i	0.42	0.87	-0.29
CYCLES			
VARIABLE	y	c	i
y	0.58	-0.87	0.30
c	-0.42	0.13	0.30
i	-0.42	-0.87	1.30

Note: A constant is also used to obtain a zero mean cycle.

TABLE 4
COMPARING RESULTS OF VARIANCE DECOMPOSITION OF INNOVATIONS:

HORIZON (QUARTERS)	% OF THE VARIANCE ATTRIBUTED TO THE PERMANENT INNOVATION FOR: (KING ET AL. RESULTS IN PARENTHESIS)		
	OUTPUT	CONSUMPTION	INVESTMENT
1	32.1 (45.0)	64.8 (88.0)	0.0 (12.0)
4	37.4 (58.0)	77.1 (89.0)	9.0 (31.0)
8	50.7 (68.0)	85.3 (83.0)	20.8 (40.0)
12	57.5 (73.0)	88.2 (83.0)	24.9 (43.0)
16	66.7 (77.0)	90.4 (85.0)	35.0 (44.0)
20	76.1 (79.0)	92.5 (87.0)	44.6 (46.0)
∞	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)

Note: The results of Table 4 in King et al.(1991) are presented in parentheses. Since trend and cycle innovations are correlated, we define the transitory innovation to be the portion of the cycle innovation which is orthogonal to the trend innovation. The permanent innovation will then be the trend innovation plus the part of the cycle innovation explained by the trend innovation. This orthogonalization method is identical to ordering the trend innovation first, i.e., cycle innovations containing the trend innovation and not vice-versa.

TABLE 5
POST-SAMPLE FORECASTING RESULTS FOR
THE RVECM AND UVECM REPRESENTATIONS

DEPENDENT VARIABLE	MEAN SQUARED ERROR (MSE)	
	RVECM	UVECM
y	0.5079	0.6099
c	0.5000	0.5889
i	3.6503	3.6772
MSE	0.1385	0.1853

Figure 1

Per-Capita Private GNP, Private Consumption and Fixed Investment
NBER Recessions Shown

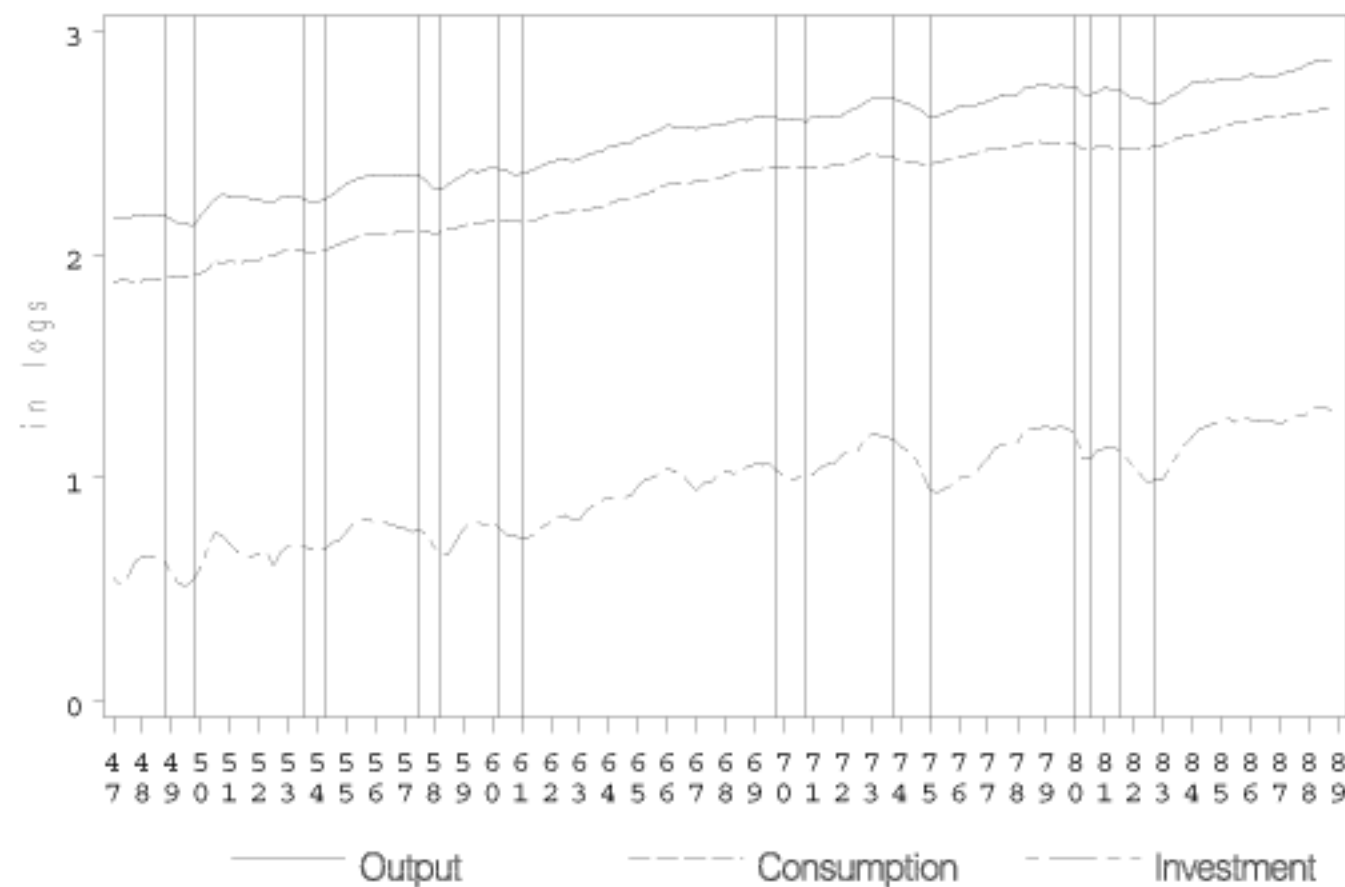


Figure 2
Per-Capita Private GNP and its Trend
NBER Recessions Shown

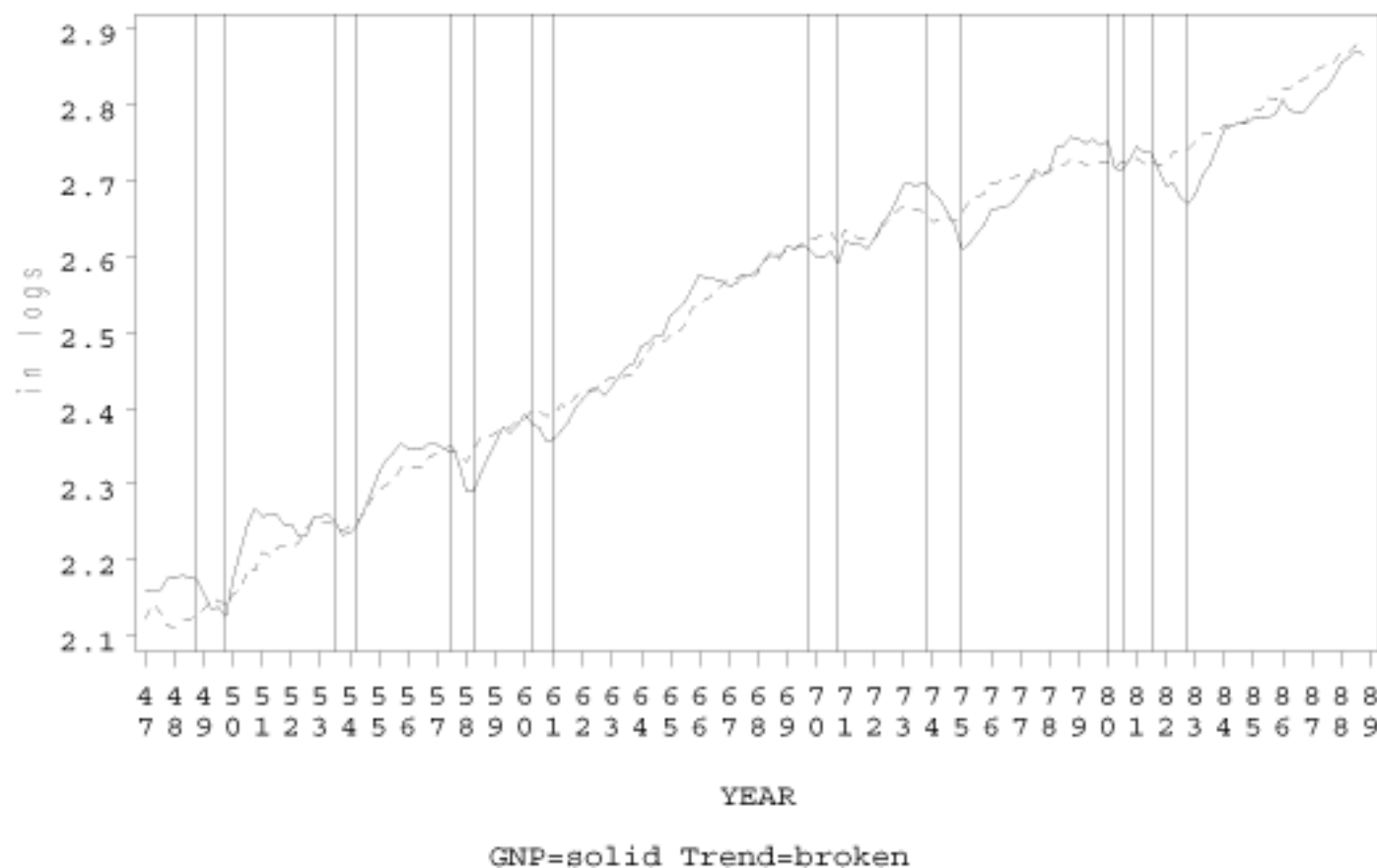


Figure 3
Per-Capita Private Consumption and its Trend
NBER Recessions Shown

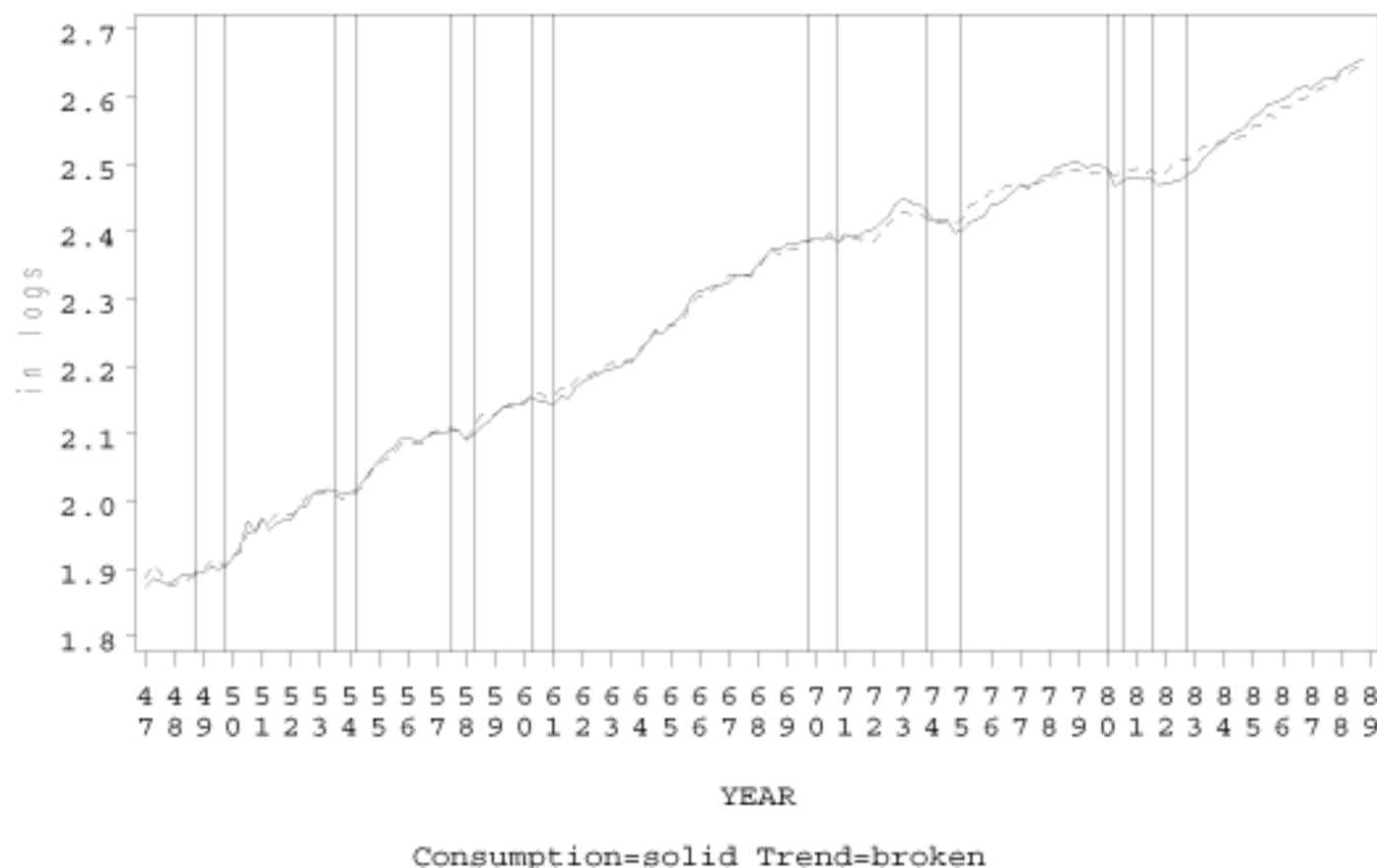


Figure 4
Per-Capita Fixed Investment and its Trend
NBER Recessions Shown

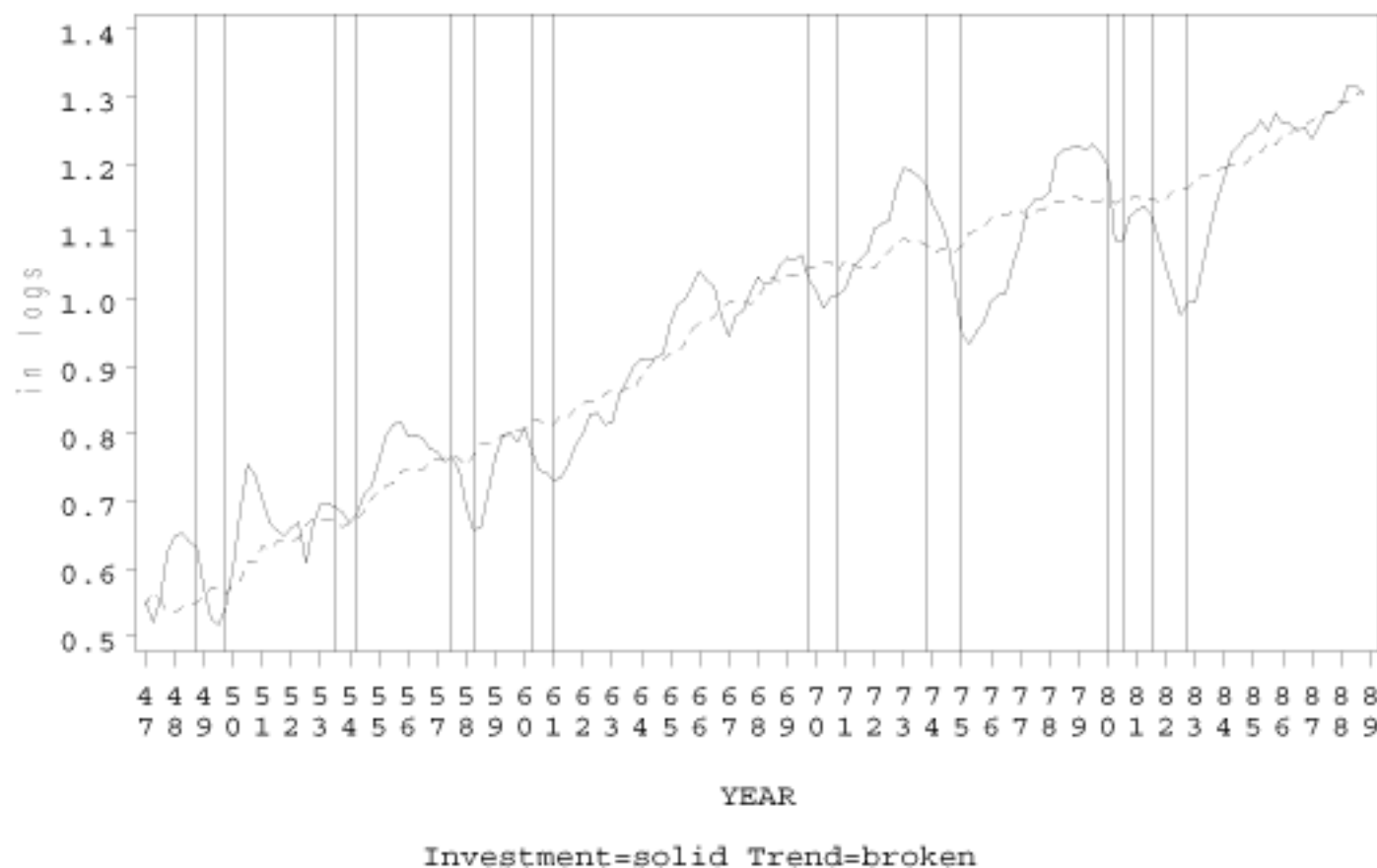


Figure 5
Cycle in Per-Capita Private GNP
NBER Recessions Shown

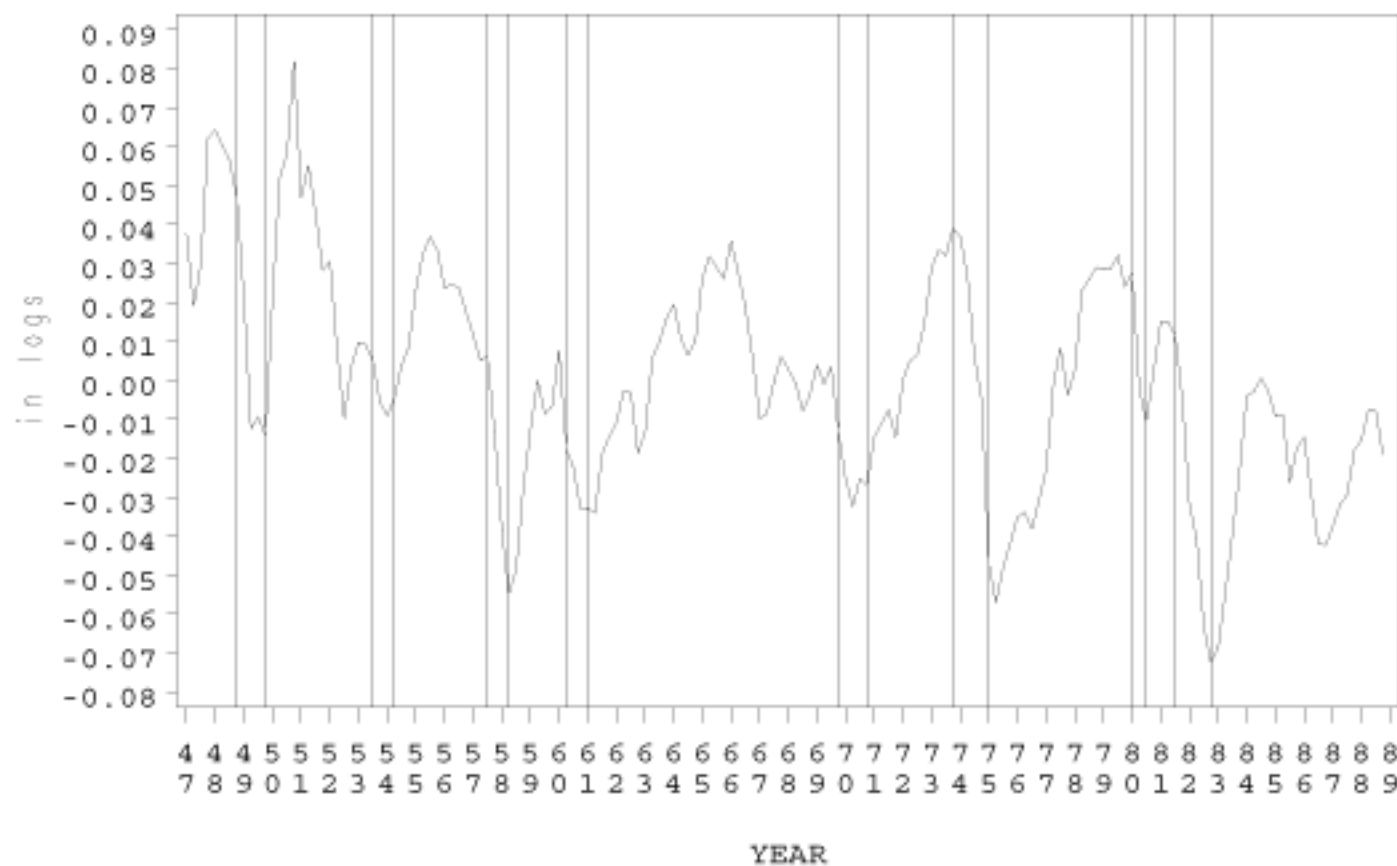


Figure 6
 Cycle in Per-Capita Private Consumption
 NBER Recessions Shown

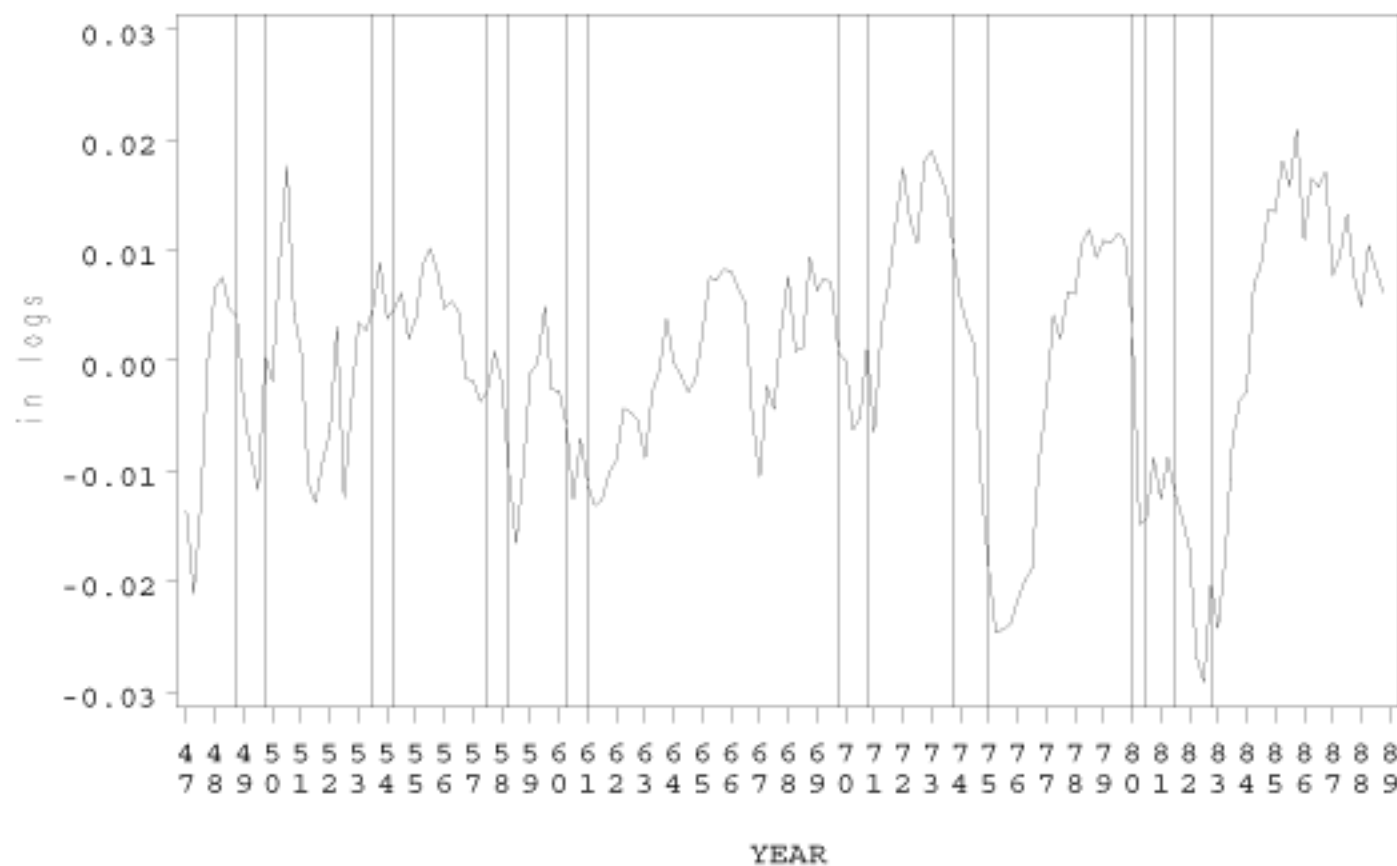


Figure 7
 Cycle in Per-Capita Fixed Investment
 NBER Recessions Shown

